

A Fusion Method of GNSS-IR Sea Surface Height Using the Carrier and SNR

Fei Yang , Weicong Chen, Ruixian Hao, Yao Du, Zhicai Li, and Sichen Zhang

Abstract—Sea surface height (SSH) can be retrieved from reflected signals of global navigation satellite systems using the interferometric reflectometry technique, in which the signal-to-noise ratio (SNR) and the carrier phase could be utilized for this inversion. How to combine them to improve the accuracy of the SSH inversion remains a key research focus, therefore, this study proposes a Bayesian-based multi-source data fusion framework that effectively combines SNR and dual-frequency carrier phase. The experiment was conducted at station AT01 in Alaska, USA, using SNR signals of S5Q and S7Q and carrier phase of L5Q and L7Q from the Galileo satellite navigation system. Three types of combinations were employed in the Bayesian fusion, including Fused-1 combining S5Q and L5Q-L7Q, Fused-2 combining S7Q and L5Q-L7Q, and Fused-3 combining S5Q, S7Q, and L5Q-L7Q. Numerical results show that single inversions with S5Q, S7Q, and L5Q-L7Q yield RMSEs of 19.83, 19.45, and 19.50 cm, respectively, while the proposed fusion method greatly improves accuracy. Specifically, the RMSE are 10.79, 11.29, and 9.23 cm for Fused-1, Fused-2, and Fused-3, respectively. The residual and Bland-Altman analyses also show that the proposed fusion method has a better performance in terms of consistency and bias. The statistics of daily RMSE show that the proposed fusion method can effectively

solve the problem of large fluctuations in single signal inversion, and can stabilize the fluctuation between 5 and 15 cm. Moreover, the proposed fusion method still achieved good results in special scenarios of flood and ebb tide. Experiments at the SC02 station demonstrate the effectiveness of the proposed method even when the single inversion already achieves high accuracy.

Index Terms—Carrier, global navigation satellite systems (GNSS) interferometric reflectometry (GNSS-IR), sea surface height (SSH), signal-to-noise ratio (SNR).

I. INTRODUCTION

GLOBAL navigation satellite systems (GNSS) continuously transmit radio signals toward the Earth's surface, which are not only used for navigation, positioning, and timing, but can also be used for ground-based remote sensing, called the GNSS-reflectometry (GNSS-R) technique [1], [2], [3]. Since Martin-Neira first proposed the feasibility of ocean altimetry using GPS reflected signals [4], GNSS-R has attracted growing interest within both the GNSS and remote sensing communities. It has been confirmed and validated in applications including sea surface height (SSH) measurement [5], wind field retrieval [6], [7], [8], soil moisture estimation [9], [10], and target detection at sea [11], [12]. It is widely acknowledged that it is of great importance for ecological environments and economic development to monitor and understand how SSH is changing. And some studies have confirmed that GNSS-R from shore-based [13], [14], airborne and spaceborne platforms can be applied to SSH monitoring [15], [16], [17]. Therefore, the GNSS-R technique will become a key approach for marine surveys and monitoring in the future due to its rich signal source and high temporal-spatial resolution observation.

The interference pattern technique (IPT) was proposed as a GNSS-R measurement type for water level monitoring [18], [19]. The extremely simple IPT is also called GNSS interferometric reflectometry (GNSS-IR), which just need one antenna to receive the composed signals of a direct signal and a reflected signal generated by multipath effects. The vertical height between the antenna and the reflecting surface, known as the reflector height (RH), is then calculated from the composed signals [20]. The composed signals cause the observed signal-to-noise ratio (SNR) data to oscillate, the frequency of which can be used to calculate RHs [21]. In 2013, Larson et al. [22] proposed to use the Lomb-Scargle Periodogram method to extract the SNR oscillation frequency and validated the efficiency of this method. Strandberg et al. [23] presented inverse modeling method of SNR data to extract the oscillation

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frequency, while the method relied on B-spline representation of the temporal SSH variations. Wang et al. [24] proposed a wavelet transform to extract the instantaneous SNR oscillation frequency, and this method can obtain instantaneous RHs with high temporal resolution. Hu et al. proposed a variational mode decomposition)-based method for SNR data spectrum analysis, and its effectiveness was subsequently validated [25], [26]. In addition, the SNR data derived from Multi-GNSS and multi-frequency could provide more redundant observations, which is helpful to improve the accuracy of SSH determinations [27].

Due to the absence of SNR measurements in many early base station observation files, the carrier phase, as another type of the GNSS observation, has also been found to be applicable for GNSS-IR, which make contributions to SSH retrieval. Ozeki and Heki [28] first used GPS to conduct the relevant experiment through the geometric linear combination of carrier phases. Then, Qian and Jin [29] extended the combination of carrier phases to GLONASS signals for the retrieval. In soil moisture retrieval, Nie et al. [30] proposed a retrieval method based on multi-satellite dual-frequency carrier phase combinations, and verified that carrier phase multipath errors are strongly correlated with soil moisture variations. Zhang et al. [31] utilized GNSS carrier phase and pseudorange multipath errors to retrieve soil moisture without separating the direct signal, demonstrating that carrier-based methods can improve the accuracy and reliability in GNSS-IR. In SSH measurement, Jin et al. [32] adopted three-frequency pseudorange combination and three-frequency phase combination from the Beidou navigation satellite system (BDS) for SSH measurement, and experimental results indicated that the combination observations achieved good accuracy of less than 0.6 m. Wang et al. [33] proposed the SSH altimetry determination based on the geometric-free linear combination of low-elevation carrier phases from fixed GPS stations, and verified that its accuracy was similar to that of the SNR inversion results. You et al. [34] proposed a tide level inversion algorithm based on triple-frequency geometry-free carrier phase combinations and verified that the carrier phase inversion results were consistent with the observed tide level trends.

Although SSH retrieval based on SNR and carrier phase observations has shown considerable potential, each single observation type still exhibits notable limitations. The retrieval based on SNR benefits from high temporal resolution, but it suffers from outlier interference which inevitably degrades its accuracy and stability [35]. The retrieval based on carrier phase is generally capable of providing high-precision results, but it is prone to being affected by abnormal phase observations, which may lead to the occurrence of outliers [31]. To address these issues, Hou et al. [36] focused on how to improve the accuracy by using signal-processing-based optimization of SNR data. He et al. [37] proposed a new fusion method, which utilized the Helmert variance component estimation (HVCE) to integrate the retrievals of the SNR and carrier phase. But a large number of iterations are often required in the HVCE to achieve convergence, which leads to significant increase in computational complexity and time in multisource and long-term data processing. Therefore, to address these limitations and improve accuracy, this study proposes a Bayesian-based fusion method

that combines SSH retrievals from both SNR and carrier phase observations, effectively suppressing outliers and improving the accuracy and robustness of SSH results across temporal scales while maintaining relatively low computational complexity.

The remainder of this paper is organized as follows. In Section II, the fundamental principles of SSH retrieval based on SNR and carrier phase observations are introduced, followed by a detailed description of the proposed Bayesian-based multi-source fusion method. In Section III, a systematic analysis of the experimental results is presented, and the effectiveness and stability of the proposed fusion method are evaluated from multiple perspectives. Section IV is dedicated to the discussion, where a station characterized by relatively high single-observation accuracy is introduced as a comparative case to further investigate the applicability and performance of the proposed fusion method under high-precision conditions. Finally, a summary of the main contributions and conclusions of the study is provided in Section V.

II. THEORY AND METHODS

A. SSH Computed By SNR and Carrier Phase

The SNR observation is highly sensitive to multipath interference, which manifests as an oscillatory component superimposed on the direct signal. After one reflection on the sea surface, one excess phase delay is introduced into the reflected signal when compared to the direct signal, leading to the generation of an interference phenomenon. The SNR of the interference signal is described by the following:

$$\text{SNR} = A_d^2 + A_r^2 + A_d A_r \cos \varphi \quad (1)$$

where A_d and A_r are the amplitudes of the direct and reflected signals, respectively, and φ is the phase difference between two signals. Here, by applying a second-order polynomial fitting to the raw SNR signal, the interference component can be effectively isolated. Assuming sea surface is static, the relative phase φ is derived geometrically from the path delay:

$$\varphi = \frac{4\pi h}{\lambda} \sin e \quad (2)$$

where λ is the wavelength of signal. With sine defined as the independent variable, the frequency of δSNR ($=A_d A_r \cos \varphi$) f_{SNR} contains the information of reflection height h , which can be expressed by the following:

$$h = \frac{\lambda f_{\text{SNR}}}{2}. \quad (3)$$

For phase multipath, a phase shift related to interference signals is modeled as follows:

$$\beta = \arctan \frac{\alpha \sin \varphi}{1 + \alpha \cos \varphi} \quad (4)$$

where $\alpha (= A_r/A_d)$ represents the amplitude attenuation factor, φ has the same meaning as variable in (2). When $A_d \gg A_r$, the phase shift is approximated as $\beta \approx 1 + \alpha \cos \varphi$. The expression of carrier phase containing β is as follows:

$$L = \lambda \psi = d + I + T - \lambda N + \lambda \beta + \varepsilon \quad (5)$$

where d , I , T are the geometric distance between satellite and receiver, ionospheric error, and tropospheric error, respectively. λ is the signal wavelength, N is the integer ambiguity, and ε represents the measurement noise. Dual-frequency phase combination is given as follows:

$$L_{1,2} = L_1 - L_2 = \lambda_1 \alpha_1 \sin \left(\frac{4\pi h}{\lambda_1} \sin e \right) - \lambda_2 \alpha_2 \sin \left(\frac{4\pi h}{\lambda_2} \sin e \right). \quad (6)$$

Both dual-frequency and triple-frequency carrier phase combinations can separate the multipath information. Similar to SNR-based methods, the dominant frequency exhibits a linear relationship with the reflection height h , expressed as follows:

$$h = a \cdot f + b \quad (7)$$

where a and b are coefficients typically obtained through simulation or fitting.

B. Proposed Fusion Method

The measurement uncertainty of SSH obtained from different types of observations can be quantified by the standard deviation of the differences between the inverted SSH time series and the corresponding reference SSH, which are provided solely as prior information and are not required to originate strictly from tide gauges, which can be depicted as follows:

$$\sigma_i(t) = \sqrt{\frac{1}{N-1} \sum_{t=1}^N (s_i^{\text{hist}}(t) - h^{\text{ref}}(t) - \bar{d})^2} \\ \bar{d} = \frac{1}{N} \sum_{t=1}^N (s_i^{\text{hist}}(t) - h^{\text{ref}}(t)) \quad (8)$$

where $s_i^{\text{hist}}(t)$ denotes the historical SSH time series obtained from the i -th observation type at time index t , $h^{\text{ref}}(t)$ represents the reference SSH at time index t , N is the number of valid inversion points for that method, and $\sigma_i(t)$ represents the standard deviation of the measurement errors of the SSH obtained from the i -th observation type relative to the reference SSH.

To define the initial condition for the Bayesian fusion, the prior mean and variance are calculated based on historical reference SSH, as shown in the following:

$$\mu_{\text{ref}} = \frac{1}{N} \sum_{t=1}^N h^{\text{ref}}(t) \quad (9)$$

$$\sigma_{\text{ref}}^2 = \frac{1}{N-1} \sum_{t=1}^N (h^{\text{ref}}(t) - \mu_{\text{ref}})^2 \quad (10)$$

where μ_{ref} denotes the prior mean of the reference SSH, and σ_{ref}^2 represents the prior variance. Given the prior distribution, the conditional probability density of the fused SSH $s_{\text{fused}}^{(t)}$ is modeled as a normal distribution:

$$p(s_{\text{fused}}^{(t)} | F(t)) \sim N(\mu_{\text{ref}}, \sigma_{\text{ref}}^2) \quad (11)$$

where $F(t)$ represents all historical information up to time t .

The posterior distributions of the SSH estimates obtained from SNR and carrier phase inversion to be fused are expressed by the following:

$$\sigma_{\text{post},i}^2(t) = \left(\frac{1}{\sigma_{\text{ref}}^2(t)} + \frac{1}{\sigma_i^2(t)} \right)^{-1} \quad (12)$$

$$\mu_{\text{post},i}(t) = \sigma_{\text{post},i}^2(t) \left(\frac{\mu_{\text{ref}}(t)}{\sigma_{\text{ref}}^2(t)} + \frac{s_i^{(t)}}{\sigma_i^2(t)} \right) \quad (13)$$

where $\mu_{\text{post},i}(t)$ denotes the posterior mean of the SSH estimates obtained from the i -th observation type, representing the optimal estimate of SSH after incorporating prior information and observational data; $\sigma_{\text{post},i}^2(t)$ represents the posterior variance of the SSH estimates from the i -th observation type, reflecting the uncertainty associated with the corresponding SSH estimates, and $s_i^{(t)}$ denotes the SSH time series of the i -th observation type to be fused at time t .

The posterior estimates of SSH obtained from SNR and dual-frequency carrier phase inversion are fused using an inverse-variance weighted scheme, yielding the fused SSH and its associated uncertainty, which can be depicted as follows:

$$\sigma_{\text{fused}}^2(t) = \frac{1}{\sum_{i=1}^n \frac{1}{\sigma_{\text{post},i}^2(t)}} \quad (14)$$

$$s_{\text{fused}}^{(t)} = \sigma_{\text{fused}}^2(t) \sum_{i=1}^n \frac{\mu_{\text{post},i}(t)}{\sigma_{\text{post},i}^2(t)} \quad (15)$$

where $s_{\text{fused}}^{(t)}$ denotes the fused SSH time series, and $\sigma_{\text{fused}}^2(t)$ denotes the variance of the fused SSH time series.

The Bayesian fusion method achieves high-precision estimation of SSH by modeling observational uncertainty and integrating data from multiple sources. The detailed process of the Bayesian fusion is shown in Fig. 1.

III. EXPERIMENT AND ANALYSIS

GNSS observations from the AT01 station were used in this experiment to retrieve SSH based on SNR and carrier phase data. The AT01 station is located in the St. Michael region of Alaska, USA, at a latitude of 63.4840° N and a longitude of 162.0064° W. It was equipped with a SEPT POLARX5 receiver, a TRM159800.00 antenna, and an SCIT antenna radome when established on 26 May 2018. The vertical distance from the phase center of the receiver antenna to sea surface is approximately 12 meters, and a tidal gauge station with the number 9 468 333, operated and managed by the National Oceanic and Atmospheric Administration (NOAA), was located 74 km from the station and records SSH at 6-min intervals. Fig. 2 shows the actual site view and the geographical correlation between the AT01 station and tide gauge 9468333. In this study, the tide gauge data were used as reference for validation. Given the local environmental conditions around AT01, this study utilized GNSS observations from an azimuth range of 0°–220° and an elevation angle range of 5°–15°.

The SNR and carrier phase of Galileo at AT01 were collected from 1 January to 31 January 2023, the inversion of each

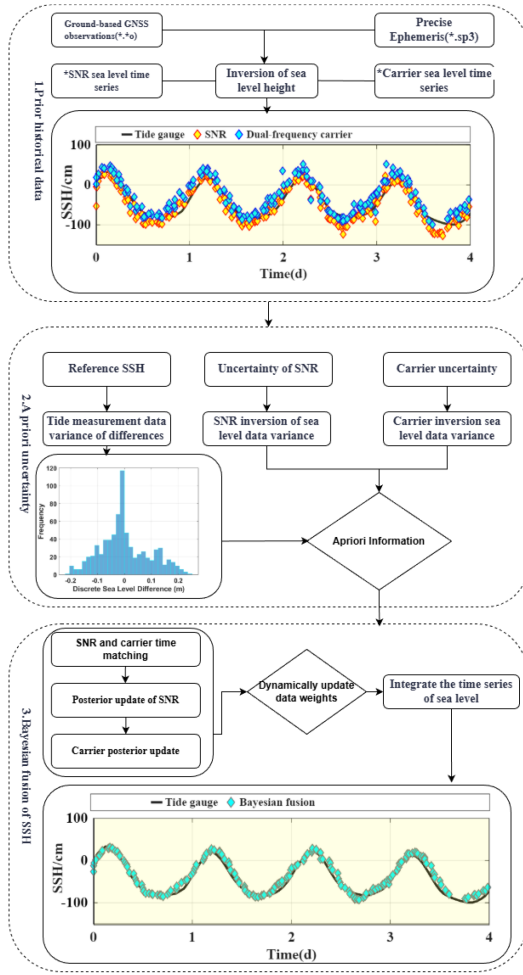


Fig. 1. Flowchart of Bayesian fusion of multisource SSH data.

SNR data and dual-frequency phase were calculated, which is illustrated in the form of boxplots in Fig. 3. These data were used solely as prior information to assess the inversion characteristics of the different observation types and were not employed as the dataset for the subsequent fusion experiment. It can be seen from the left panel that the length of box and the range of bound in S8Q are much larger than those in the other SNR results, indicating a relatively low inversion accuracy of this type of SNR. Specifically, the median values are close to 10 cm for S1C, S7Q, S6C and S5Q, while the value reached 33 cm for S8Q. Then, six types of dual-frequency carrier phase were selected, including L1C–L5Q, L1C–L6C, L1C–L7Q, L5Q–L6C, L5Q–L7Q, and L7Q–L6C. It can be seen from the right panel that the inversion result of the L1C–L6C has obvious systematic bias, with the first and third quartiles as well as the upper and lower bounds being much smaller than 0. Therefore, the carrier phase and SNR of L5 and L7 on Galileo were selected based on the above analysis, as this ensures that the subsequent fusion research could utilize the SNR and carrier phase with good inversion, and ensures that the SNR and carrier of the corresponding frequency can be obtained simultaneously.

Based on the prior inversion analysis, the period from 1 February to 3 March 2023, was selected as the fusion interval.

Fig. 4 presents the retrieval results of SSH based on SNR and dual-frequency carrier phase, in which the upper panel showed the complete SSH time series retrieved from three types of observations by different colors along with the records from tide gauge. It can be seen that the retrieved SSH generally ranged from -150 to 150 cm, with a maximum tidal range that exceeded 280 cm. In terms of long-period variations, it demonstrates that the SSH retrieved from both SNR and dual-frequency carrier phase has strong consistency with the tide gauge records, indicating that both methods were capable of effectively capturing low-frequency SSH trends. However, the retrieval accuracy of the two methods varied across different time periods. To further examine the capability of these two methods in capturing short-period tidal dynamics, a magnified view from 6 February to 11 February was shown in panel (b), which corresponds to a period of relatively stable SSH variations. Overall, the SSH retrievals remained consistent with the tide gauge observations, and the fluctuating nature of the SSH retrieval points was clearly observed. It is a magnified view from 16 February to 21 February in panel (c), which is correspond to a period of intense SSH fluctuations. It showed that the performance of both methods was significantly degraded under these conditions, especially during 18 February to 20 February, during which both the three types of SSH retrievals failed to capture the fluctuating variations. Therefore, although single retrievals based on traditional SNR and dual-frequency carrier phase could capture SSH variations, their accuracy was affected by tidal dynamics, leading to degraded performance.

Therefore, three types of combinations were employed in the proposed Bayesian fusion in this experiment, including Fused-1 combining S5Q and L5Q–L7Q, Fused-2 combining S7Q and L5Q–L7Q, and Fused-3 combining S5Q, S7Q, and L5Q–L7Q. The SSH results of the proposed fusion method were illustrated in Fig. 5, the three panels of which are aligned along the same time axis as in Fig. 4 to facilitate a better comparison of SSH results before and after the fusion. Panel (a) showed the complete SSH time series for the three fusion combinations, with different fusion results distinguished by colors. The SSH from all three fusion combinations exhibited high consistency with the tide gauge records in terms of long-period variations, indicating that the Bayesian fusion method could effectively combine historical information from single SNR and carrier phase retrievals, thereby capturing SSH trends more accurately. Panel (b) shows that during periods of relatively stable sea surface, the SSH results from the three fusion combinations were highly consistent with each other, exhibiting minimal differences. All three fusion results closely matched the tide gauge records, with the maximum deviations for Fused-1, Fused-2, and Fused-3 being 25.90 cm, 24.50 cm, and 17.90 cm, respectively. Panel (c) illustrated that during periods of intense sea surface fluctuations, the SSH results from all three fusion combinations generally matched the variability of the tide gauge records. The maximum deviations for Fused-1, Fused-2, and Fused-3 were 35.20 , 36.70 , and 34.50 cm, respectively, indicating that although the deviations increased under highly dynamic conditions, the overall trends of the fused results remained well aligned with the tide gauge records. This demonstrated that the proposed Bayesian fusion

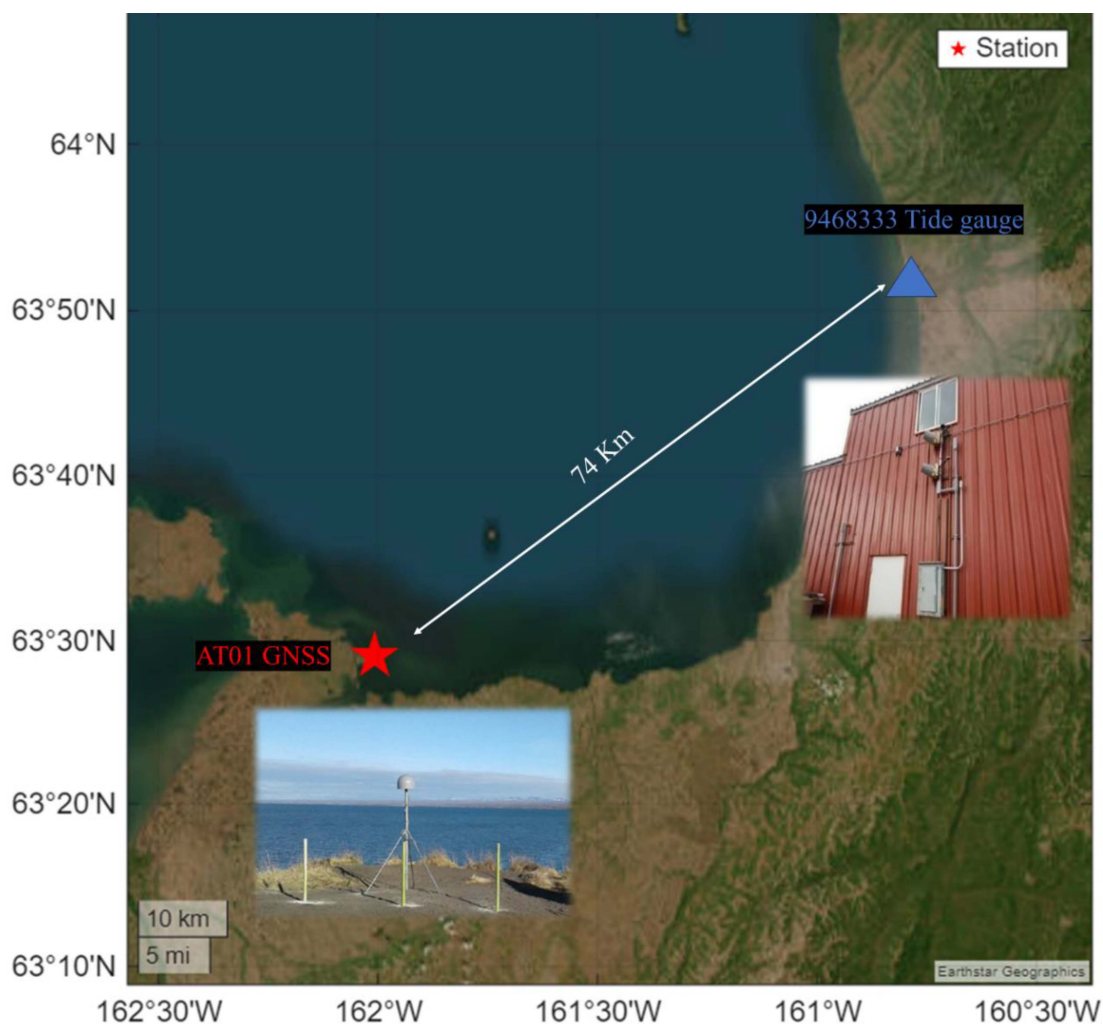


Fig. 2. Schematic diagram of AT01 station (image from <https://www.sonel.org>, basemap from earthstar geographics).

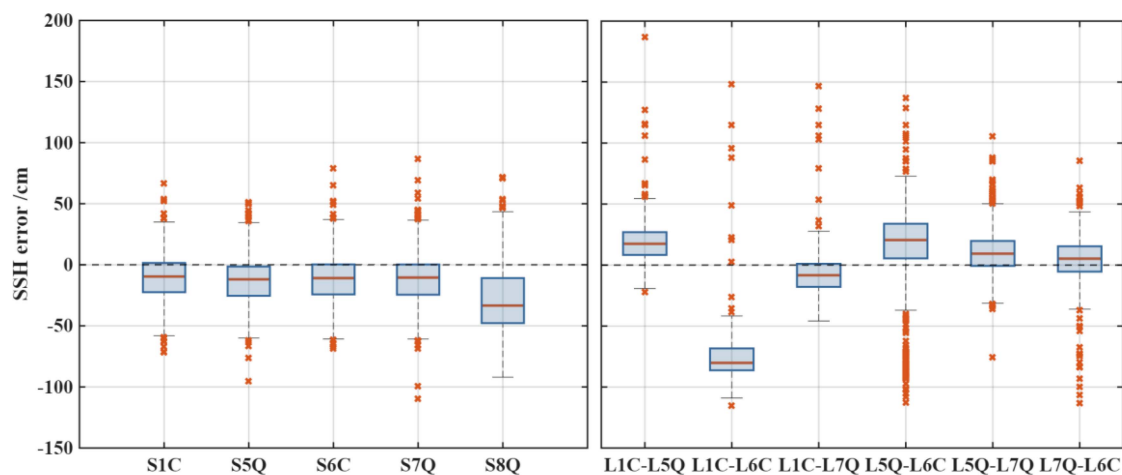


Fig. 3. Boxplot of Galileo system SNR by frequency band and dual-frequency carrier phase inversion results at AT01 station from 1 January to 31 January 2023.

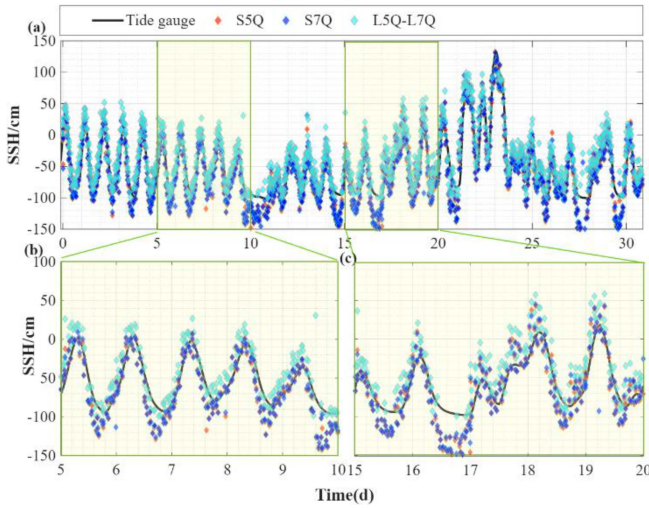


Fig. 4. (a) Time series of Galileo system S5Q, S7Q, and L5Q–L7Q SSH inversion results at AT01 station from 1 February to 3 March 2023; (b) SSH inversion results from 6 February to 11 February 2023; and (c) SSH inversion results from 16 February to 21 February 2023.

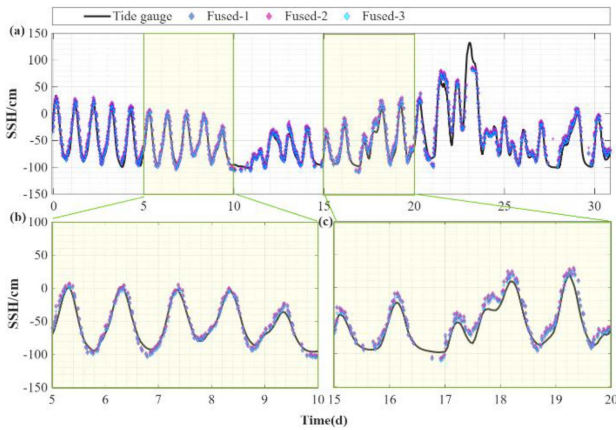


Fig. 5. (a) Time series of SSH for the three fusion combinations; (b) results of the three fusion combinations from 6 February to 11 February 2023; and (c) results of the three fusion combinations from 16 February to 21 February 2023.

method significantly improved the accuracy of SSH retrievals and effectively reduced the impact of tidal dynamics.

To further examine the effectiveness of the proposed Bayesian fusion, the residual histograms of the three single retrieval results and the three fusion combinations were presented in Fig. 6. From the upper three panels, it was observed that the residuals of the three single retrieval results were mainly distributed within the range of -50 to 50 cm. Among them, the mean residuals of S5Q and S7Q were found to be close, with values of -8.3 and -7.20 cm, respectively, while the mean residual of L5Q–L7Q reached 14.20 cm, indicating relatively low residual accuracy. From the lower three panels, it showed that the residuals of the three fusion combinations were primarily distributed within the range of -20 to 20 cm, and the distributions were densely concentrated around zero, which demonstrated that the proposed fusion method significantly improved the residual accuracy of the SSH time series. Among the three fusion combinations, the mean residuals of Fused-1 and Fused-2 were close in value, with

their standard deviations differing by only 0.12 cm. Fused-3 exhibited the best performance, with a mean residual of 2.5 cm and a residual accuracy that was significantly higher than those of Fused-1 and Fused-2, highlighting the advantage of multisource data fusion.

The scatter plots were further utilized to compare the SSH retrievals from three single inversion results and three fusion combinations using the records from the tide gauge as reference in Fig. 7, in which the black dashed line denoted the ideal reference 1:1 line and the red solid line represented the linear regression fit. The fitting equation, correlation coefficient, root mean square error (RMSE), and mean absolute error (MAE) were provided in the upper left corner of each panel. From the upper three subplots, it was evident that the single inversion results generally exhibited underestimated slopes, with the scatter points distributed more diffusely and some deviating considerably from the reference line. The RMSE values all exceeded 19 cm, and the correlation coefficients were below 0.9 , indicating relatively large overall errors. In contrast, the lower three subplots showed that all three fusion combinations substantially improved the SSH accuracy, with the scatter points more densely clustered and closely aligned with the reference line. The correlation coefficients of the three combinations were all around 0.95 , while both RMSE and MAE were markedly reduced compared with the single inversions. Among them, Fused-3 achieved the best performance, with an RMSE of 9.23 cm and an MAE of 7.24 cm, demonstrating the significant advantage of multisource data fusion in improving inversion accuracy.

The Bland–Altman analysis was a method used to evaluate the agreement between two measurement techniques by plotting their differences against their averages. To further examine the effectiveness of the Bayesian fusion, the Bland–Altman analysis was applied to the comparative evaluation of SSH data, in which the time series obtained from three single retrievals and three fusion combinations were compared with tide gauge records. As shown in Fig. 8, the X-axis represented the mean of the two measurements, while the Y-axis represented their difference. The mean difference (MD) and the limits of agreement (LOA) were employed to quantify consistency, with the LOA defined as $MD \pm 1.96 \times SD$, and narrower LOA values indicating better agreement between the two methods. In the figure, the light blue circles denoted the SSH data, the black solid line indicated the mean difference, the blue dashed lines represented the LOA, and the specific upper and lower values were marked in red. The results showed that the scatter distributions of the three single retrievals in the upper panels were relatively dispersed and exhibited systematic biases: the mean differences of S5Q and S7Q were -8 and -7 cm, respectively, with LOA ranges of approximately 77 cm, while the mean difference of L5Q–L7Q reached 14 cm with an LOA range of 70 cm. In contrast, the scatter distributions of the three fusion combinations in the lower panels were more concentrated and closely aligned around zero, with significantly narrower LOA ranges: the LOA widths of Fused-1, Fused-2, and Fused-3 were 34 , 35 , and 34 cm, respectively. Among them, Fused-3 achieved the smallest mean difference of about 2 cm, along with the narrowest agreement interval. Compared with the single retrievals, Fused-3 reduced

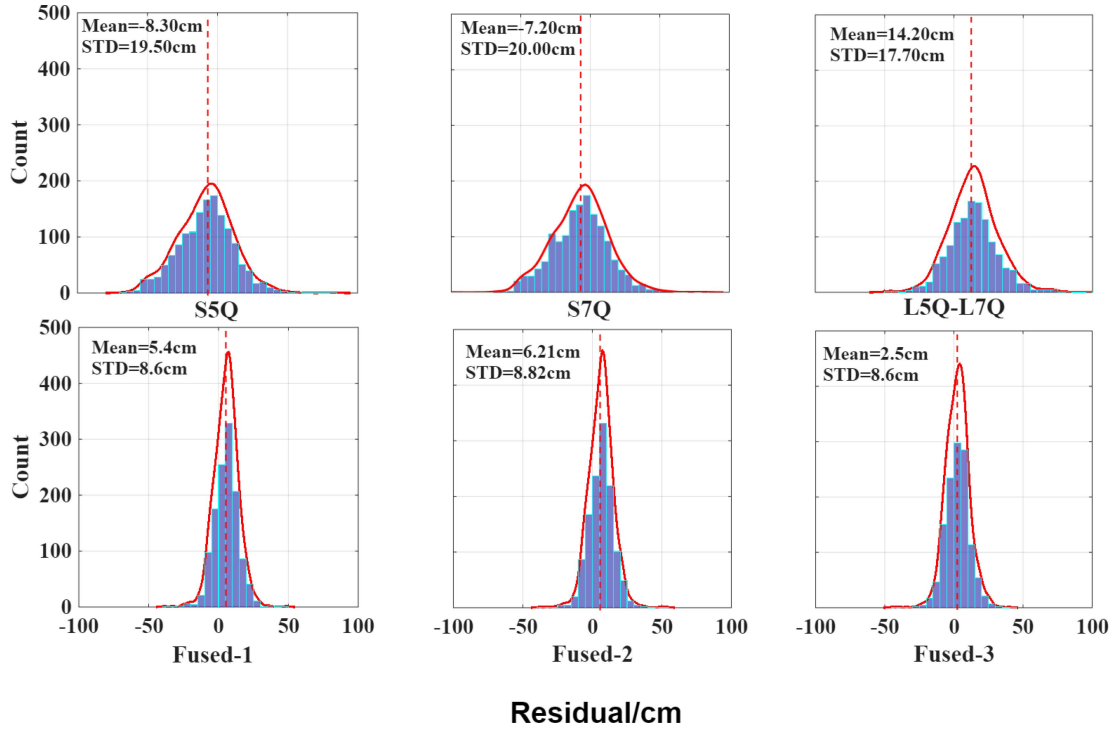


Fig. 6. Residual histograms of the three single inversion results and the three fusion combinations.

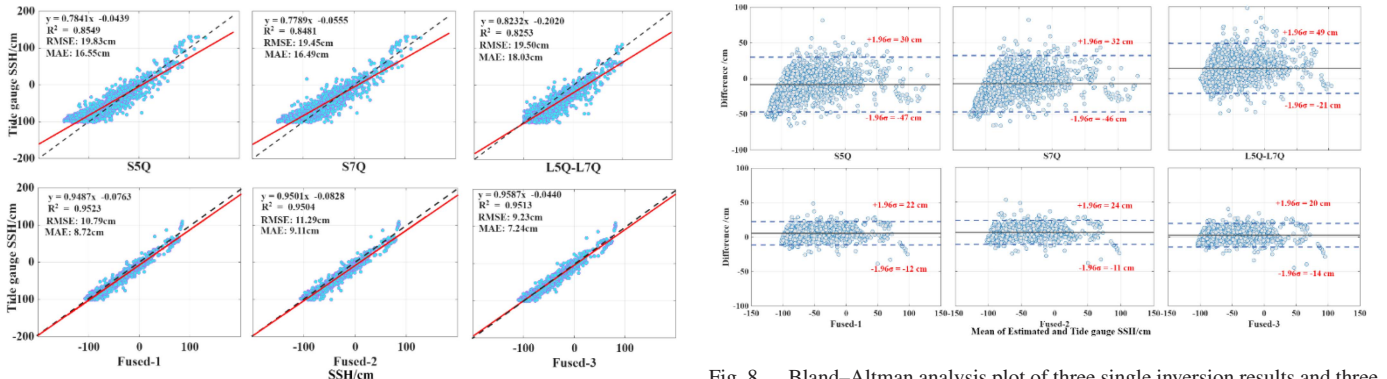


Fig. 7. Scatter plots of three single inversions and three fusion combinations.

the LOA range by approximately 56% relative to S5Q and by about 51% relative to L5Q-L7Q. These results demonstrated that Bayesian fusion substantially reduced both systematic bias and random error, thereby improving the consistency between the inversion results and the tide gauge records.

To clearly evaluate the accuracy of different methods in terms of daily SSH result, Fig. 9 illustrated the variations in daily RMSE over time for the three single inversions and the three fusion combinations. The horizontal axis represented time, while the vertical axis denoted RMSE, ranging from 0 to 40 cm. The results showed that the three single inversions generally exhibited relatively large RMSE fluctuations, with values mainly distributed between 15 and 30 cm and occasionally exceeding 30 cm, indicating lower accuracy and insufficient stability. Among them, the L5Q-L7Q dataset produced consistently

higher errors, with most values exceeding 20 cm and reaching a maximum close to 35 cm around day 22. The S5Q and S7Q results were relatively similar, with RMSE values mostly ranging from 15 to 30 cm, though strong fluctuations were still evident. In contrast, all three fusion combinations significantly reduced the RMSE levels, which remained consistently between 5 and 15 cm with only minor temporal variations, thereby demonstrating higher stability and reliability. Among them, Fused-3 maintained the lowest RMSE in almost all periods, with most values falling below 10 cm, and achieved the best overall performance throughout the entire period, highlighting its dual advantage in both accuracy and stability. Fused-1 and Fused-2 performed at levels comparable to Fused-3 in most cases, but local peaks appeared around days 5 and 22, where RMSE temporarily rose to 15–20 cm, suggesting slightly inferior performance relative to Fused-3 in those intervals. Overall, all three fusion combinations

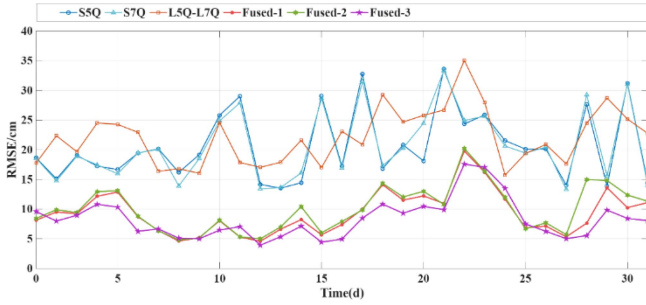


Fig. 9. Daily RMSE plots of three single inversion results and three fusion combinations.

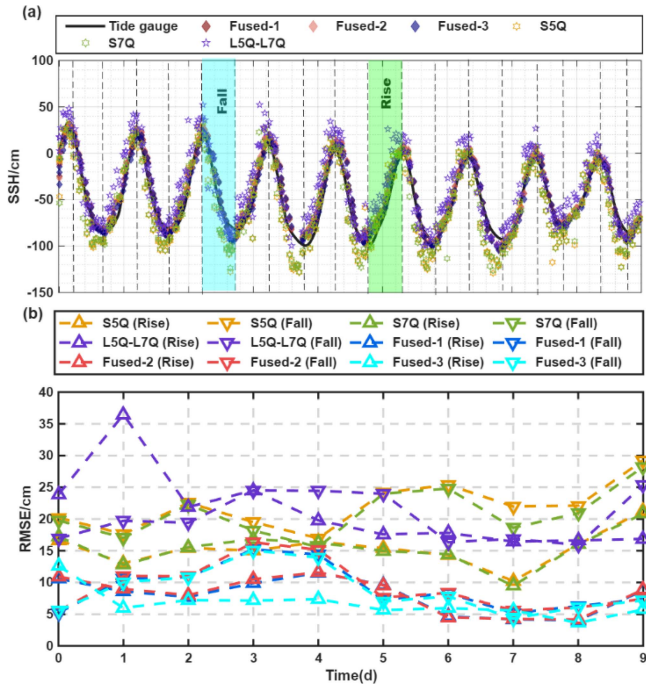


Fig. 10. (a) Comparison of the time series of three single inversion results and fusion combinations from 1 February to 10 February 2023; and (b) daily tidal variation RMSE plots during the same period.

substantially improved daily error characteristics compared with single inversions, with Fused-3 achieving the most superior performance, thereby further confirming the advantage of multisource data fusion in enhancing SSH accuracy and stability.

To further evaluate the performance of different methods during rising and falling tides, the analysis focused on a representative period covering 1 February to 10 February 2023. Fig. 10 consisted of two parts, with the upper panel (a) showing the point-by-point comparison of SSH variations during this interval and the lower panel (b) presenting the corresponding daily RMSE for the rising and falling tide stages. Panel (a) illustrated the tide gauge record as a black solid line, while different colors and symbols represented the three single inversions and the three fusion combinations. Overall, the fusion-derived curves followed the tide gauge records more closely throughout the tidal cycles, particularly at the turning points of high and low

tides, where both phase and amplitude errors were substantially reduced. In contrast, the single inversions showed systematic biases, with S5Q and S7Q tending to underestimate and L5Q–L7Q tending to overestimate, especially near high tide where the deviations became more evident and scatter increased. Blue shading indicated the falling tide stages, while green shading highlighted the rising tide stages, enabling a direct comparison of differences between the two tidal phases.

Panel (b) quantitatively compared the daily RMSE of different methods during rising and falling tides. The results showed that the single inversions exhibited generally higher RMSE values with pronounced fluctuations, mostly distributed within the range of 15–35 cm. Among them, L5Q–L7Q consistently produced larger errors with distinct peaks, whereas the RMSE of S5Q and S7Q mainly ranged from 15 to 25 cm. By contrast, all three fusion combinations significantly reduced the RMSE, which remained between 5 cm and 15 cm with minor temporal variations, indicating greater stability and reliability. In particular, the Fused-3 consistently achieved the lowest RMSE during both rising and falling tides, with most values below 8 cm, while Fused-1 and Fused-2 showed overall comparable performance but were still inferior to Fused-3 in certain rising and falling tide stages. Overall, observations from panels (a) and (b) suggested that single inversion methods were more susceptible to systematic deviations and extreme residuals during rising tides, especially near high tide, likely due to unstable reflection geometries and related factors. In contrast, Bayesian fusion effectively suppressed both systematic biases and random noise through the complementary use of multisource information, thereby achieving markedly superior performance over any single inversion in both tidal phases. Among the fusion combinations, Fused-3 demonstrated the most robust and accurate performance across different tidal conditions.

IV. DISCUSSION

To further evaluate the effectiveness and reliability of the proposed method, validation analyses were also conducted at the SC02 stations. The SC02 station is located in Washington State, United States, at a latitude of 48.5462°N and a longitude of 123.0076°W. To validate the retrieved SSH, tide gauge measurements were obtained from the Friday Harbor station, which is operated and maintained by the NOAA. The Friday Harbor tide gauge is located approximately 345 m from the SC02 station and provides high-quality in situ sea level observations with a temporal resolution of 6 minutes. Based on the local environment and surrounding reflecting surfaces, GNSS observations within an azimuth range of 50°–230° and an elevation angle range of 3°–13° were selected to ensure data quality. The experiment was conducted at the SC02 station. To ensure consistency with the AT01 station, the same signal combination strategy was adopted, using SNR signals of S5Q and S7Q and carrier phase observations of L5Q and L7Q from the Galileo system. Three types of combinations included Fused-1 combining S5Q and L5Q–L7Q, Fused-2 combining S7Q and L5Q–L7Q, and Fused-3 combining S5Q, S7Q, and L5Q–L7Q. The retrieval results from January 1 to January 31, 2024 were used as prior information,

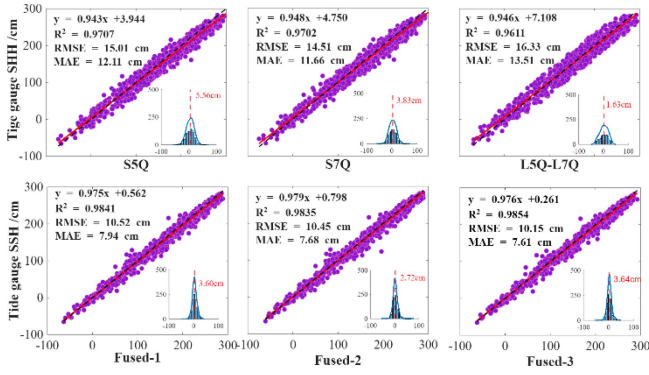


Fig. 11. Combined scatter plots and residual distributions of three single inversions and three fusion combinations at the SC02 station.

while the fusion was conducted over the period from 1 February to 3 March 2024.

As illustrated in Fig. 11, at the SC02 station, the correlation coefficients of the three fusion combinations are all higher than 0.98, while both RMSE and MAE are significantly reduced compared with the single inversion results. This indicates that the proposed fusion method can provide stable performance improvements under different station conditions. Compared with the AT01 station, the single inversion results at SC02 already exhibit higher retrieval accuracy. Nevertheless, further improvements are still achieved through data fusion in terms of both error reduction and correlation enhancement. A more detailed analysis based on residual distributions reveals that systematic biases still exist in the single inversion results. The residuals of the single-signal inversions exhibit an approximately bell-shaped distribution with relatively large dispersion, indicating the presence of noticeable systematic deviation and random fluctuations. In contrast, the residual distributions of the three fusion combinations become more compact and sharply peaked, showing a cone-like concentration pattern with most residuals clustered near zero. This demonstrates that data fusion not only reduces bias but also effectively suppresses variability, leading to improved stability and consistency of the retrieval results.

Among the three fusion combinations, Fused-3 achieves the best performance, with an RMSE of 10.15 cm and an MAE of 7.61 cm. Compared with the single inversion result from S5Q, the RMSE decreases from 15.01 cm to 10.15 cm, corresponding to a reduction of approximately 32.4%, while the MAE decreases from 12.11 to 7.61 cm, corresponding to a reduction of approximately 37.2%. Combined with the residual analysis, it can be observed that although Fused-2 achieves the smallest median bias, Fused-3 performs better in terms of overall error metrics including RMSE and MAE. This indicates that Fused-3 is more effective in reducing random errors, thereby achieving superior overall performance. These results further confirm that multi-source data fusion is effective not only in reducing systematic bias but also in improving overall retrieval accuracy.

V. CONCLUSION

A Bayesian fusion method for SSH results was developed in this study by utilizing multisource GNSS observations,

including SNR and carrier phase data. The processing workflows for different observation types were explicitly defined, together with the specific strategies employed for SSH fusion. The method was evaluated using observational data from the AT01 and SC02 stations, and validation was performed with tide gauge records.

At the AT01 station, it was found that, although the single inversion results were able to capture the overall trend of SSH variations, their performance varied across different periods, and accuracy was significantly degraded under strong tidal dynamic conditions. Systematic biases and random fluctuations were commonly observed in the single inversion results, indicating pronounced limitations during short-period tidal variations. In contrast, all three fusion combinations consistently outperformed the single inversion results. The fused results not only enhanced the capability to suppress short-period SSH fluctuations, but also exhibited improved stability during both flood and ebb tides. Single inversion results were found to be more susceptible to outliers, with more pronounced deviations observed during flood tide conditions. By comparison, the adverse effects of outliers were effectively mitigated through complementary multisource data fusion, resulting in significantly improved accuracy and reliability.

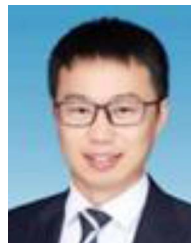
To further validate the effectiveness of the proposed method, comparative experiments were conducted at the SC02 station. The results showed that, even under conditions where the single inversion results already exhibited high accuracy, the proposed Bayesian fusion method was still able to achieve further improvements in precision. The fused results consistently exhibited reduced errors and enhanced correlation, indicating that the method remains effective under high-quality observational conditions. This further suggests that the proposed approach possesses stable refinement capability across different data quality levels, thereby demonstrating its general applicability.

In summary, the effectiveness and robustness of the proposed Bayesian fusion method for multisource SSH time series fusion were demonstrated across different stations. The limitations of single inversion methods were effectively mitigated, and significant improvements in both accuracy and stability of SSH estimates were achieved. The proposed method provides a reliable reference and strong support for multisource data fusion in GNSS-IR-based sea surface height monitoring applications.

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